



#### PREDICTIVE MODELING FOR BUSINESS PROCESSES

DESIGNING AND EVALUATING AN INTERPRETABLE PREDICTIVE MODELING TECHNIQUE FOR BUSINESS PROCESSES





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#### MOTIVATION

PREDICTIVE MODELING FOR BUSINESS PROCESSES? WHY?

- Early warning systems
  - Predict future behavior
  - Warn managers if future is bad
  - Intervention possible
- Anomaly detection systems
  - Predict future behavior
  - Warn managers if a surprising future has happened
  - Analysis / Intervention possible



#### LITERATURE

#### TRANSITION SYSTEM MINING







#### LITERATURE

#### FREQUENCIES ANNOTATED







#### LITERATURE

#### COMPLETION TIMES ANNOTATED





# ABSTRACT PRINCIPLE





#### MAIN PROBLEM

DIMENSIONALITY REDUCTION <-> PROCESS DISCOVERY

- Dimensionality reduction
  - Map event log to a useful feature set
- Question: What is a good process discovery algorithm for predictive modeling applications?





#### **TWO APPROACHES**

**GRAMMATICAL INFERENCE THEORY** 

Process = set of valid event sequences



 Process = probability distribution over event sequences



#### **TWO APPROACHES**

**GRAMMATICAL INFERENCE THEORY** 

 Strong language bias necessary



#### Weaker language bias possible





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#### **PROBABILISTIC MODELS**

#### Hidden Markov Model (HMM)



# Probabilistic Finite Automaton (PFA)





## **PFA ESTIMATION**

**3 FAMILIES OF METHODS** 

- Bayesian inference
  - Do not estimate a single model (e.g., Gibbs sampling)
  - But: effective!
- Parameter estimation
  - Estimate parameters (often: ML estimation)
  - Quite effective too
- State merging
  - Iteratively merge states, starting with prefix tree
  - Least effective

Verwer, S., Eyraud, R. & de la Higuera, C., 2013. PAutomaC: a probabilistic automata and hidden Markov models learning competition. *Machine Learning*.

#### **PFA MODIFICATIONS**





#### **PFA MODIFICATIONS**





 $P(Z_{0}) \sim Categorical(\pi_{0}, ..., \pi_{K})$   $P(X_{t}|Z_{t} = k) \sim Categorical(b_{k0}, ..., b_{kE})$   $P(Z_{t}|Z_{t-1} = k, X_{t-1} = e) \sim Categorical(a_{ke0}, ..., a_{keK})$   $P(\pi_{1}, ..., \pi_{K}) \sim Dirichlet(\rho_{1}, ..., \rho_{K})$   $P(b_{k1}, ..., b_{kE}) \sim Dirichlet(s_{k1}, ..., s_{kE})$   $P(a_{ke1}, ..., a_{keK}) \sim Dirichlet(r_{ke1}, ..., r_{keK})$ 

## **EVALUATION (PREDICTION)**



Event log	Predictor	Accuracy	ØSensitivity	ØSpecitivity	н
2012 W	EM	0.719	0.578	0.955	11.183
	5-gram	0.728	0.588	0.957	Infinity
2012 A	EM	0.801	0.723	0.980	3.093
	4-gram	0.801	0.723	0.980	2.839
2012 O	EM	0.811	0.647	0.973	4.513
	3-gram	0.811	0.647	0.973	4.180
2013 Incidents	EM	0.714	0.383	0.974	12.041
	4-gram	0.635	0.377	0.967	Infinity
2013 Problems	EM	0.690	0.521	0.945	7.231
	3-gram	0.699	0.564	0.948	Infinity

#### DEMONSTRATION

- Visualization is possible
- Threshold
  Cut out improbable transitions
- Also possible: Petri net synthesis
  - -> Petrify

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## **EVALUATION (PROCESS DISCOVERY)**



Algorithm	Fitness	Advanced behavioral appropriateness
EM + Petrify	0.998	0.908
AGNES-Miner	0.995	0.813
α+	0.969	0.873
α++	0.984	0.879
DT Genetic Miner	0.996	0.778
Genetic Miner	0.998	0.737
HeuristicsMiner	0.973	0.809
ILP Miner	1.000	0.786

De Weerdt, J. et al., 2012. A multi-dimensional quality assessment of state of-the-art process discovery algorithms using real-life event logs. *Information Systems*, 37(7), pp.654-676.

#### Conclusion



- Goal: Devlelop a good "event sequence -> state" reduction for predictive modeling in BPM
  - Probabilistic approach
  - Weak language bias
- Probabilistic finite automaton (PFA)
  - Modified (start/end state + regularization)
  - Estimation with EM
  - Can be used as process discovery algorithm
- PFA can be better than n-gram approaches...
- ... but does not have to be!



# Questions?

# Slides available at: http://goo.gl/Bi99Ck

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